An Efficient Model for Fruit Quality Assessment in Small-Scale Agriculture Using Deep Learning

Synopsis of the Research Proposal

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ABSTRACT

Fruit quality affects farmers, distributors, consumers, and the economy as a whole, making it a crucial component of the agricultural supply chain. In addition to being more visually pleasing, high-quality fruits offers improved food safety and nutritional content, both of that directly improve consumer satisfaction and market value. By growing high-quality fruits, farmers, particularly small-scale farmers, can increase their income and long term sustainability. The traditional method, based on manual inspection of fruit quality requires significant effort and considerable time and possibility to human errors. These approaches are not feasible to satisfy the expanding needs of current agriculture operations, and that are inconsistent.

Two subset of Artificial intelligence, Machine learning (ML) and deep learning (DL) makes it possible to automate the task of fruit quality assessment. These technologies enable the accurate, efficient, and trustworthy classification and evaluation of fruits based on a range of attributes, such as color, texture, shape and size, using digital photographs. The deep learning model, Convolutional neural networks (CNNs) are deep learning models that are currently being utilized successfully in agriculture and have demonstrated remarkable performance in image recognition tests.

The aim of research is to design an efficient model, considering the limitations of available methods in small-scale agriculture to assess the quality of fruits. By accelerating the quality assessment process, the proposed system will be helpful to reduce post-harvesting losses and to support in decision-making.

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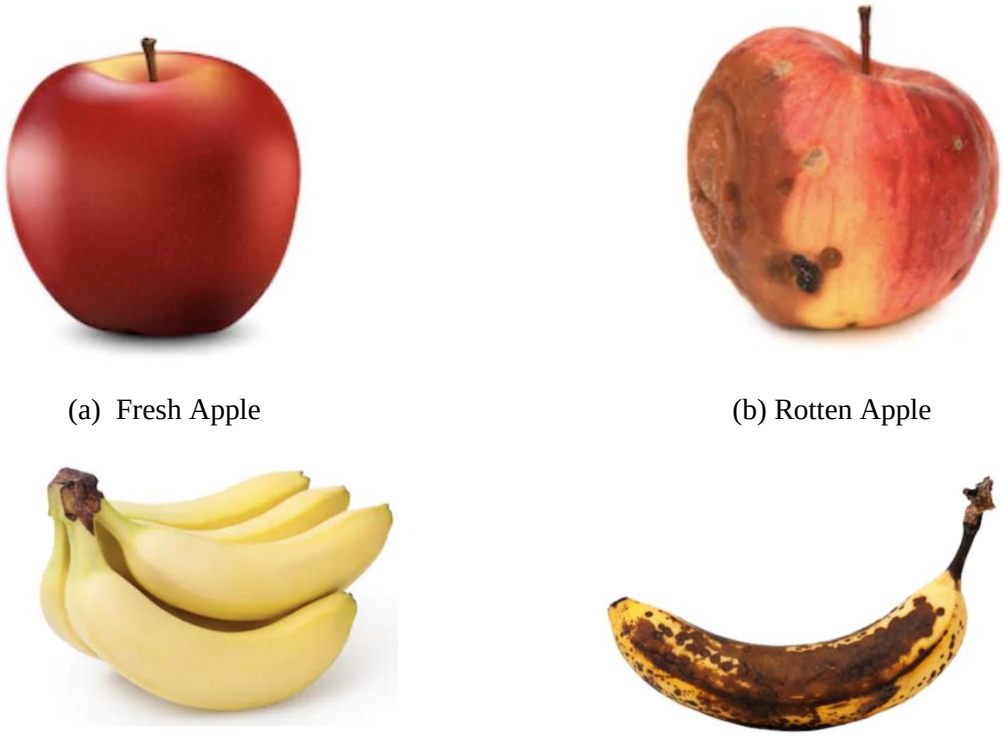
1. INTRODUCTION

Fruit quality refers to the overall characteristics of a fruit that determine its freshness, taste, appearance, nutritional value, safety, and suitability for consumption or market sale. It includes both external attributes, such as color, size, shape, firmness, texture, and absence of defects, and internal attributes, such as sweetness, acidity, aroma, juiciness, nutritional content, and internal damage. It is a key factor that affects consumer acceptance, market value, storage performance, and food industry standards. [1].The sample images (a), (b), (c) and (d) showing the quality of fruits in figure 1.1 [2].



(a) Fresh Apple (b) Rotten Apple

(c) Fresh Banana (d) Rotten Banana

Figure 1.1: Sample images of fresh and rotten fruits

1.1 Need of fruit quality

Fruit quality is essential because it directly influences consumer health, market value, and the overall efficiency of the post-harvest supply chain. High-quality fruits are safe to eat, rich in nutrients, and free from defects such as bruising, rotting, or contamination. Maintaining good quality allows farmers and sellers to earn higher profits, reduces rejection rates during sorting and export, and increases customer satisfaction. It also helps extend the shelf life of fruits, ensuring they remain fresh during storage, transportation, and retail display. Proper quality assessment reduces food waste by identifying damaged or spoiled fruits early. In modern agriculture, fruit quality evaluation supports automation through computer vision and deep-learning-based grading systems, making sorting faster, more accurate, and cost-effective. Overall, fruit quality is necessary to safeguard health, improve economic returns, support sustainable food systems, and meet the growing demand for consistent, high-standard produce [3, 4].

1.2 Fruit quality assessment

Fruit quality assessment is the process of evaluating fruits to determine their freshness, ripeness, safety, market value, and overall acceptability based on physical, chemical, sensory, and sometimes technological parameters. It helps identify whether a fruit is suitable for consumption, storage, processing, or sale. The assessment examines both external qualities such as color, size, shape,

firmness, texture, and defects, and internal qualities such as sweetness total soluble solids (TSS), acidity, aroma, nutritional content, and internal defects [5].

1.3 Fruit Quality Assessment Methods

Fruit quality assessment methods are broadly categorized into traditional (destructive and manual) and modern (non-destructive and technological) methods [6].

1.3.1 Traditional Methods

Traditional methods involve visual inspection, where trained graders evaluate external attributes such as color, size, shape, defects, bruises, and overall appearance. Physical tests—including firmness measurement using penetrometers, weight determination, and texture evaluation—are also widely used. Chemical analysis helps measure internal attributes such as TSS using a refractometer, titratable acidity (TA), Potential of Hydrogen (pH), moisture, and nutrient content, while sensory evaluation is performed by panels that assess taste, aroma, juiciness, and consumer acceptance.

1.3.2 Modern Methods

Modern methods focus on non-destructive and automated techniques. These include computer vision(Machine Learning and Deep Learning) and image processing to analyze color, size, shape, and surface defects; spectroscopy methods (Near-Infrared(NIR), hyperspectral, multispectral) to assess internal quality like sweetness, firmness, and internal browning; electronic nose and electronic tongue systems for aroma and flavor profiling; and machine learning or deep-learning-based models that classify fruit quality, ripeness, and defects automatically.

1.4 Limitations of Traditional Fruit Quality Assessment Methods

Traditional methods of fruit quality assessment have several important limitations that reduce their effectiveness, especially in modern small-scale, large-scale agricultural and industrial environments. These methods rely heavily on manual visual inspection, which is subjective and varies from person to person, leading to inconsistency and lack of repeatability. Many commonly used physical and chemical tests—such as firmness testing with a penetrometer, TSS measurement with a refractometer, or acidity titration—are destructive, meaning the fruit being tested is damaged or cannot be sold afterward, resulting in additional waste. Traditional techniques are also time-consuming and labor-intensive**,** making them unsuitable for fast, high-volume sorting or continuous monitoring. They generally fail to detect internal defects such as internal browning, fungal infection, and hidden bruising because most evaluation focuses only on external appearance. Furthermore, laboratory-based chemical analyses require trained personnel, specialized equipment, and controlled conditions**,** which increases cost and limits use in field conditions. Due to these limitations, traditional methods cannot provide rapid, objective, scalable, or non-destructive assessment, leading to the growing adoption of modern automated and sensor-based technologies [7].

1.5 Challenges in Small-Scale Agriculture for Fruit Quality Assessment

The key challenges faced by small-scale agriculture (small farmers, small orchards, local markets) in fruit quality assessment are [8]:

- **Limited Access to Advanced Technology**

Small farmers often cannot afford high-end tools like hyperspectral cameras, firmness testers, or automated sorting machines. This results in continued reliance on manual visual inspection.

- **Skill Gaps and Limited Training**

  Small farmers often lack adequate technical knowledge of important fruit quality parameters such as Total Soluble Solids (TSS), firmness, acidity, and common defects. Many also receive limited training in operating even simple quality assessment instruments like refractometers and penetrometers. In addition, insufficient understanding of post-harvest physiology—such as ripening behavior, respiration rate, and factors contributing to decay—further restricts their ability to evaluate fruit quality effectively. As a result, the assessments performed at the farm level are frequently inaccurate or incomplete, leading to inconsistent grading and reduced market value.

- **Cost Constraints**

  Even low-cost tools (₹1,500–₹10,000 range) can be expensive for small farmers to invest in Non-destructive sensors, portable testing devices, storage and grading equipment.

- **Market Pressure and Middlemen Influence**

  Small farmers rely heavily on local traders (middlemen).The prices are influenced by subjective judgments, leading to unfair quality-based pricing and loss of profit due to inconsistent quality claims.

1.6 Solutions to Small-Scale Agriculture for Fruit Quality Assessment

Small-scale farmers cannot afford hyperspectral cameras or industrial graders. There is need of a tool that can overcome the challenges facing by small-scale agriculture farmer for fruit quality assessment. The issue can be can solve by introducing free-of-cost, Deep Learning and image-driven quality assessment technique. With deep learning and applying image processing a method can be provide to deal with fruit quality assessment problem. The research focus to develop a deep-learning model that uses images to assess the quality of fruits [9-11].

1.6.1 Deep learning DL

Deep learning is a branch of artificial intelligence inspired by machine learning and the structure of the human brain. Artificial Intelligence (AI) is a branch of computer science that focuses on creating machines or software that can perform tasks that normally require human intelligence. Machine Learning (ML) is a branch of Artificial Intelligence where computers learn patterns from data and make predictions or decisions without being explicitly programmed.

Deep learning uses Convolutional Neural Networks (CNNs) and for complex tasks in computer vision and image analysis. It automatically performs feature extraction and transformation through multiple nonlinear processing layers, where the output of each layer becomes the input to the next. Deep learning models perform exceptionally well when trained on large datasets, enabling them to learn complex patterns and variations, and to achieve high accuracy in object detection tasks. Among these models, CNNs are widely used for image classification, object detection, and segmentation, as their convolution layers extract important features such as edges, textures, and shapes, while

pooling layers reduce spatial dimensions to lower computational complexity. The extracted features are then passed to fully connected layers for final classification, and dropout layers are often used to prevent overfitting by randomly deactivating neurons during training [12].

1.6.2 Image processing

The steps involves in fruit quality assurance using image processing are mentioned in Figure 1.2. [13-17]

Figure 1.2. Processes of fruit recognition.

1.6.2.1 Fruit image acquisition

The fruit images can be from direct capturing by digital camera, mobile phone camera or from dataset (Kaggle, Mendeley, etc).

1.6.2.2 Image pre-processing

In this step collected fruit images having noise, different size, poor lighting and low contrast are pre-processed by noise removal, image normalization image resizing, brightness and contrast adjustment.

1.6.2.3 Image segmentation

The goal of image segmentation is to separate the fruit from the background and other objects in the image using a mask to exclude background information or applying thresholding based on gray levels. In deep learning the segmentation is optional because CNNs can learn features directly from raw images without explicit segmentation.

1.6.2.4 Feature extraction

From the segmented images the physical characteristics are identifies and quantifies in this step. The color, size, shape and texture are the main classes of features. Deep learning based algorithms uses the concept of feature extraction for classification task.

1.6.2.5 Classification/Quality prediction

In this step a model or algorithm uses the extracted features and determines the fruit quality like good, bad, fresh or rotten.

2. LITERATURE REVIEW

A comprehensive review of existing research conducted by examining papers published in reputed journals such as IEEE Access, Sensors, Horticulture, Applied Sciences, and Agronomy. These studies were analyzed to understand the current state of fruit quality assessment, evaluate the methodologies used, and identify significant achievements in the field. The review highlights both the strengths and the limitations of used methods. This analysis provides a strong foundation for identifying research gaps and formulating improved approaches for fruit quality assessment in small-scale agriculture.

Fischer-Brandies, L. et al. [18] (2025) proposed a transfer learning based model with VGG16, MobileNetV3 and ResNet50 CNN as binary classification model for identification of fresh and rotten fruits. Gaussian filter is applied for performance enhancement. The model performance measured as 99%. There was false prediction available with each model and only binary classification was done. The model is limited with 8 fruit types, no detection in multi fruit images and missing of explainability.

Tapia-Mendez, E. et al. [19] (2025) introduced a system in which over 200 training iteration, **t**he dataset of 39 fruit and classes of vegetable for training and assessment of various object detection architectures are used. Study used DDQ and DINO provided good result, and outperformed over traditional YOLOv3 and YOLOv4 models with a mAP of 0.65. ROC curve analysis was utilized to confirm their classification reliability beyond mAP; the DINO model obtained an AUC of 0.89 and the DDQ obtained an AUC of 0.95, showing strong performance in for fruit classification tasks.Proposed study needs to expand the scope of the dataset and increase the visual diversity as the study used only 1535 images with imbalance class distribution.

Alves, V. C. D , E. et al. [20] (2025) proposed method used for pineapple fruit quality evaluation by using ANN,MP5,REPTree decision tree, random forest, SVM and Zero R algorithms and achieved accuracy was 0.7.The SVM provided good result but model is limited only for pineapple.

Almutairi, A. et al. [21] (2024) developed an advanced model that is capable for detecting and classifying different varieties of Rutab date fruit in an accurate and efficient manner to become fully fluffy. The YOLOv8 model has provided better result over YOLOv5 and YOLOv7 models. The model provides methods for classification, sorting, and quality control. Recall, precision, and F1-score measures have been utilized to analyze the correctness of this investigation. The experimental data shows that YOLOv8 achieves, a mean Recall of 0.99 percentage and Precision of 0.991 percentage with an Intersection over Union (IoU) colored in the range [0-1]. It also achieves a mean Average Precision of 0.994 percentages, a mean Average Precision of [0.5:0.95], and a mean average precision of [0.5:0.85].The tiny size of the dataset and the fixed angles employed for image capture are the drawbacks and included 9 types of date fruits only.

Gao, X., Li et al. [22] (2024) developed and verified a deep learning-based approach for detecting and assessing Apple defects and quality.This system combines a number of cutting-edge machine learning and image processing algorithms to deliver an accurate and efficient automated detection solution that is suited to the real-world for Apple business requirements. The development of a comprehensive system that integrates Maximum Entropy Selection Optimization, Jump- Connection-Attention Mechanism and Jump-connection-SAM model, and is the primary contribution of this study. The extensive experimental validation showed the potential uses of deep learning technology in agriculture and offered crucial technical

support for practical production. The system's ability to handle complicated images was significantly enhanced by this integration, with special proficiency in the vital tasks of quality assessment and apple defect segmentation. The technique achieved 93% precision, 90% recall, 91% accuracy, and 92% mean Intersection over Union (mIoU) in the defect-segmentation experiments, greatly outperforming traditional model of deep learning such as U-Net, SegNet etc. .When tested for grading in term of quality, proposed method also showed great efficiency, attaining 90% recall and accuracy and 91% precision. The technique has not yet been implemented, despite experimental data demonstrating that the system outperforms existing methods. Apple maturity level detected on two geographic locations and harvest seasons that should be enhanced for broader natural variations.

Khullar, V. et al. [23] (**2024)** developed a model to classified fruits in good and poor categories of online image dataset. The study used two models with two datasets. For the first model the accuracy was 99.49% and for the seconf model the accuracy was 99.75% for first dataset. The accuracy of fist model reported 85.43% and second model with 96.75% for second dataset. The study focuses on binary classification and lack of explainability.

Zhao, M. et al. [24] (**2024**) introduced a portable fruit ripeness prediction system that uses deep convolutional neural networks (DCNN) and colorimetric sensing combinatorics to precisely determine fruit maturity. The DenseNet was applied to evaluate fruit ripeness on collected colorimetric sensor image data and shown accuracy of 97.93% for the validation and 82.20% for the testing. When used in conjunction with a DCNN, this fruit ripeness prediction method effectively tackles the problems of low identification accuracy and complex pattern recognition. The system performance is depending on selected fruit i.e. Banana, Peach, and Mango variety, for more generalization requires large dataset size with different fruit types.

Tai, N. D. et al. [25] (2024) developed ML algorithm to provide the grade and sort the mango fruits based on external features. In order to extract exterior mango features, various image processing algorithms are first applied. These features are then combined with weight values from sensor signals to create the dataset. After that, numbers of machine learning algorithms are tested on the dataset to identify most reliable ones. Following that, numbers of ensemble-learning methods are used such as stacking, boosting, and bagging. Models are then assessed and contrasted to determine which one best fits the dataset used in this investigation. The evaluation of errors in the experimental section shows how beneficial image processing algorithms are. The evaluated model claims 0.9855 precision, 0.9901 recall, and 0.9863 F1-score. External features like color, size and defects are focused in the study while ripeness feature is missing. Mangoes from multiple farms in a particular area made up the training and testing dataset, which may not be generalizable to other mango kinds, geographical areas, harvest circumstances, or handling procedures.

Rybacki, P. et al. [26] (2024) suggested a CNN architecture and the DateNET model to automatically classify five different types of date palm fruits according to their geometric attributes and color. The choice of categorization criteria affected the model's validation accuracy in the investigation. The accuracy for color based fruit classification reported as 85.24%, for geometric features it was 87.62%.The accuracy reported 93.41% when the color and geometry feature taken into account. The model training and validation done on limited dataset of 500 images of 5 date varieties with controlled image environment. Despite improvement in accuracy, the average classification time (27.89 ms/image) is higher than the existing model like MobileNet.

Karaja, M. B. et al. [27] (2024) proposed deep learning based method for lemon quality prediction. Study used the CNN model we created, which was trained using the InceptionV3 architecture, to extract features from pictures of lemons. About 2533 photos of lemons and an empty surface make up the dataset utilized in the study. It is separated into training, test, and validation data and contains pictures of both high-quality and low-quality lemons in different lighting conditions and reported model accuracy of 99.74%.The study used only on fruit with binary classification (good quality, bad quality).

Karthikeyan, M. et al. [28] (2024) presented a modified Yolov3 technique was developed for the recognition of apple fruit during harvesting and production in food industry. The spatial pyramid method and swish activation function are then applied in detection layer for enhancement of yolov3 model performance. This allows for the differentiation of various apple varieties and the separation of damaged apples from healthy ones. A mean precision of 99.13% is attained. The paper uses small dataset of 1800 labeled images of apple, and only one fruit is tested. The results focus on mean average precision (mAP) and speed but do not examine interpretability, model transparency, or explainability, which are important in deploying AI for critical agricultural workflows.

Sangeetha, K. et al. [29] (2024) suggested a method to classify fresh and rotten apple, banana, mango and orange was proposed by use of CNN and deep learning techniques. The model performance is evaluated using precision, recall and F1 score parameters. The result was suggested as 0.74. 0.70 and 0.71 respectively. Research focused on limited number of fruits and no real world images was collected.

Azadnia, R. et al. [30] (2023) recommended a deep learning and machine vision oriented method was for quality assessment of hawthorn fruit by using unripe, ripe and overripe levels. To improve the deep learning performance, the augmentation technique applied following the pre-processing phase, the proposed. To grade the hawthorn fruit Inception-V3 and ResNet-50 were utilized. The Inception-V3 network outperformed the other classifiers, surpassing the overall validation accuracy of 100% when compared to alternative techniques. The study focused on one fruit, images captured with smart phone in fixed chamber. The study used small dataset of 600 images that augmented upto 3000.

IOSIF, A. et al. [31] (2023) presented a custom model for apple quality assessment. For training and testing, a dataset of more than 2000 apple photos with the labels "Good" and "Damaged" was assembled. In order to maximize performance parameters like accuracy, precision, and recall, the study looks into different architectures and hyper parameter settings for a number of CNN models. The analysis of the study highlights ML algorithm's capability for apple quality assessment procedures by showing that the MobileNet and Inception models produce the highest levels of accuracy. The customized model reported 0.91 training accuracy with 0.91 training F1 score, 0.92 validation accuracy and 0.90 validation F1 score. The study is limited to one fruit and suffers with explainabilty.

Verma, P. K. et al. [32] (2023) presented an automated method for detecting the quality of mango fruit by using Internet of Things and artificial intelligence technology. To take the images of mango fruits, a hyperspectral image camera was used and to examine the pictures the image processing method are used. Mango fruit is categorized using deep learning algorithms according to quality attributes including size, color, and freshness. The proposed CNN3D model achieved 0.53 accuracy on days one and two, 0.25 accuracy on days three and four.Hyperspectral imaging requires sophisticated and costly equipment. The research is limited to mango fruit only.

Mohd Ali, M. et al. [33] (2023) suggested a multimodal data fusion framework based on feature extraction from thermal imaging that uses deep learning techniques to determine pineapple quality. In order to create the deep learning models, features that were extracted from the thermal pictures and showed a relationship with the fruit's quality attributes were chosen. To classify pineapple varieties based on the features retrieved by resilient network are combined for multimodal data fusion network, three distinct deep learning architecture types—ResNet, VGG16, and InceptionV3—were constructed. Multimodal data fusion outperformed all other deep learning architectures in terms of classification accuracy, with a score of 0.9687. InceptionV3, VGG16, and ResNet had similar results. Training and testing relied on a relatively small, curated dataset of 1,080 pineapple fruits from a single orchard, which can be the cause of restriction of generalization of suggested model for other varieties.

Alsirhani, A. et al. [34] (2023) proposed a novel classification method for date fruit classification using deep transfer learning. There are 27 classes and 3228 photos in the collected dataset. There are five steps involve for experimental result. In the first step, the pixel intensity and color distribution are used with conventional machine learning techniques, to analyze the accuracy. In second step, a deep transfer learning method are applied to optimize the date fruit classification by model. In order to choose the optimal retraining point, the feature extraction portion of the model was refined in the third step by applying various retrained points. The model's fully connected layer was adjusted in the fourth step to produce the optimal categorization configurations. In step fifth with regularization the resulting model achieved validation and test accuracy as 97.21% and 95.21% respectively. The study is limited to date fruit only which shows limited diversity.

Sangeetha, M. et al. [35] (2023) developed a prototype that uses a thermal camera and a smartphone camera to automatically take pictures of fruits, producing two different datasets: RGB and thermal. Image processing, ML, and DL have used to classify fruits and detect bruises. A second set of RGB image and thermal image files are used in order to evaluate quality and self-life. The proposed work uses several texture features based on gray-level co-occurrence matrix (GLCM) to improve fruit categorization and fault detection systems. For GLCM dependent qualities in fruit classification, Random Forest outperformed K-Nearest Neighbor, while RGB images outperformed thermal images. The color and texture features are used by RF and KNN algorithms to identify images. The classification accuracy of GLCM based features shown 96.40% and the RGB based features classify images with 97, 24% accuracy. The prediction accuracy of the KNN and RF algorithms is 81.70 and 84.12 percent, respectively, with kappa values of 79.97 and 81.86 percent. The best method for categorizing fruit using a collection of thermal images is RF.The dataset is relatively small as 1870 samples per set for 11 fruit classes.

Jadhav, S. et al. [36] (2023) used ResNet50 as pre-trained CNN model because it supports hundreds or thousands of convolutional layers to deal with complex image processing tasks.
The accuracy and loss percentages improved with use of ResNet50 model, indicating that in learning the patterns and attributes necessary for identifying the fruit quality, the suggested model was successful. This demonstrates that deep learning in general and CNNs in particular can handle difficult image classification jobs. The accuracy percentage of VGG16 86%, ResNet 85%, Xception 98% was suggested .The existing classification standards do not include fine-grained quality attributes such as ripening stages beyond simple good or/bad, or disease/grading information beyond outward appearance.

Gulzar, Y. [37] (2023) offered a method which used 26,149 images of 40 different fruit varieties dataset. The test set and training set are split into a 3:1 ratio and replicated at random. The project modifies the MobileNetV2 architecture by adding a customized head with five distinct levels. For classification purpose the MobileNetV2 model customized and the TL-MobileNetV2 was developed. Moreover, pre-trained model is maintained through transfer learning. With an equal error rate of only 1%, customized model outperforms MobileNetV2 by 3%, and achieved 99% accuracy. The accuracy performance has shown better than that of AlexNet, VGG16, InceptionV3, and ResNet. Additionally, the TL-MobileNetV2 model achieved a 99% F1-score, 99% precision, and 99% recall. In conclusion it is observed that dropout method can help to minimize the overfitting in transfer learning, and that transfer learning is a major factor in improving performance. The model has not been validated on images from field, market, or supply chain environments. Scalability and computational efficiency for large-scale or real-time applications, particularly on low-resource hardware or mobile devices, are discussed.

Amin, U. et al. [38] (2023) proposed an automated system using deep-convolutional-neural network (DCNN) for classification of fruit freshness. For developing a reliable method to evaluate quality of fruits, the authors employed transfer learning of the CNN model AlexNet. While fine-tuning, they adjusted a few hyperparameters and saw an improvement in their algorithm's performance. Our refined CNN model by transfer learning produced higher accuracy when other parameters, including learning rate and batch size, were changed. All three datasets showed very positive results from the proposed model, shown accuracy 98.2%, 99.8%, and 99.3% percentages on the datasets presented above respectively. Additionally, the model is computationally efficient, taking an average of 8 ms to get the classification result. The study used limited fruit variety to judge fresh and rotten fruit and multi-class .There are only a few fruit types in the dataset, which can limit applicability to other types and classification into multiple classes can be performed. Research does not provide explainability features, such as visualizations of model decisions or explanations of which image regions influence freshness classification.

Tapia-Mendez et al. [39] (2023) developed an advance model by using deep learning techniques to identify the maturity of different fruits and vegetables. Two different kinds of systems employ the MobileNetV2 architecture. 32 fruit and vegetable groups can be classified by the system, and six fruit and vegetable classes can have their ripeness determined by a different technique. To forecast the fruit or vegetable class and maturity respectively .Results shown 100% accuracy ,98% precision ,99% recall , and 99% F1-score , to assess the ripeness and with 97.86% accuracy , 98% precision,98% recall ,and F1-98% F1-score for fruit and vegetable classification. Despite the outcomes the method having number of restrictions. Only small number of classes of ripening classes for fruit and vegetables are considered, the model can be improved with inclusion of some more ripening stages. The system can be used a single model for fruit and vegetable quality assessment in pace of using two different model. There is lack of explainabilty feature in proposed system.

Worasawate, D. et al. [40] (2022) suggested the k-mean, naïve Bayes, support vector machine, and feed-forward artificial neural network (FANN), four popular machine learning (ML) classifiers, with the goal of identifying the mangoes' maturity stage during harvest. Initially the model was trained on biochemical data then ML classifiers are evaluated on electrical and physical data. To compare the model’s performance four-fold cross validation was applied. With of 89.6% mean accuracy for the unripe, ripe, and overripe classes, the FANN classifier outperformed the other classifiers. The study done for only for mango fruit with low accuracy.

Aherwadi, N. et al. [41] (2022) used two datasets of banana fruit: the first is self-created, while the second, called Fruit 360, is sourced from Kaggle. There are 2100 photos in our dataset, divided into 700 ripe, unripe, and over-ripe photographs. The image augmentation was applied for increasing the dataset size upto 18900 images. By using image augmentation the two DL algorithms (CNN and Alex Net) are combined. For CNN model 98.25% accuracy and for AlexNet 81.75% accuracy was achieved for original dataset.In augmented dataset 99.36% accuracy for CNN and 99.44% accuracy for AlexNet was recorded. Similarly 81.96% accuracy by CNN and 81.75% accuracy by AlexNet model was achieve for Fruit-360 dataset. Suggested approach is only tested for bananas.

Albarrak, K. et al. [42] (2022) presented a CNN-based system that is capable for classification of 8 distinct, well-liked fruits in the Saudi Arabia country. With a frequency ranging from 204 to 240 per girl, on an internal dataset comprising more than 1750 photos of eight distinct date fruits, the proposed system was trained. The suggested model incorporates various preprocessing strategies, including weakening learning rate, model's check pointing, picture augmentation, and dropout, to increase the performance. The proposed categorization model implemented using an existing architecture (MobileNetV2) and 99% accuracy was shown by the use of proposed model. The model is tested for date fruit only with small dataset size.

Nithya, R. et al. [43] (2022) developed a computer vision system that is based on CNN's deep learning model and ML algorithms for identification of mangoes defect. The system was tested on 800 mango photos. The proposed system can efficiently detect defective mangoes, as discussed in experimental result. After being tested on 800 mango photos, the suggested CNN deep learning based system achieved classification accuracy of 98.5%.The model is evaluated for Kent mangoes fruit only also the model is tested on small dataset.

Kumar, T. B. et al. [44] (2022) proposed a deep learning model for fresh and damaged fruit classification. For Apples, Oranges and bananas, the proposed CNN model is capable to identify fresh and rotten one. The datasize for model implementation was taken of 8400 images. The accuracy achieved by the suggested model is 97.14%.The model is restricted to limited fruit types and provides binary classification only.

Mukhiddinov,M. et al. [45] (2022) recommended a model based on YOLOv4 for multiclass classification of fruit and vegetable. The model classifies image object into 2 categories that are fresh and rotten. An optimized YOLOv4 model, a fruit and vegetable image dataset, data argumentation, and performance evaluation are all part of the suggested solution. For faster and more accurate identification, the Mish activation function was applied to strengthen the core model in additionally. The experimental evaluation of suggested technique can yield a greater average precision as 50.4% and 49.3% and 41.7% than the original YOLOv4 and YOLOv3 model, in comparison to the preceding YOLO series. The system struggles to accurately distinguish between fruits and vegetables that have very similar color, shape, or texture. Majority of test images (about 85%) are single objects with plain backgrounds, which does not fully represent real-world conditions.

Kumar, A. et al. [46] (2021) proposed a new architecture based on DL .For sorting the fruit and evaluation purpose in real word fruit images a Fruit CNN approach is used and achieved test accuracy of 99.6%.When compared to the most advanced deep learning models, the proposed system requires very less time for training the sizable dataset and testing fruit images, demonstrating its broad usefulness in precision agriculture. It is also possible to train

more fruit images from various classes with fewer parameters that can provide fast training of model and also reduces the processing time. The model is a black-box CNN without any explainable AI (XAI) component to interpret why a fruit is classified as “good” or “bad”. The model performs static image classification and does not track fruit growth or ripening stages.

Chakraborty, S. et al. [47] (2021) suggested a method to identify the rottenness of fruits from input fruit images. For this study oranges, bananas and apples fruits are used. For feature extraction CNN are used and for classification purpose Max pooling, average pooling and MobileNetV2 architectures are used. The 99.46% training accuracy and 99.61% validation accuracy achieved by using MobileNetV2.Using Max pooling 94.49% training accuracy and 99.61% validation performance was suggested. In addition the training accuracy of 93.06% and validation accuracy of 93.72% reported in average pooling. The results shown that the MobileNetv2 achieved higher performance in examination performed on Kaggle dataset. The suggested system is able to classify fresh and rotten fruits. Only three types of fruits (apple, banana, orange) are tested in the study and no explainability or interpretability was shown.

Ashtiani, S. H. M. et al. [48] (2021) introduced a technique for classification of two mulberry on the basis of black and white genotyped classification, compared for various CNN based model for ripening phases. The models that were reassessed include DenseNet, Inceptionv3, ResNet-18, ResNet-50, and AlexNet. The models evaluated by using 1000 photos of each genotype and total 2000 fruit dataset was evaluated. Model training conducted by using 70 percentage of the dataset. Three metrics was used for performance analysis named classification time accuracy and loss. Tested models included DensNet,ResNet-18,Inseption-v3 and ResNet-50. The use of Transfer-Learning improved the models, resulting in higher classification accuracy. The highest performance noted for AlexNet and ResNet-18 for ripeness assessment of black and white mulberries, provided 98.32 percentage and 98.65 percentage of accuracy respectively. Additionally, combining datasets from both genotypes did not impact the performance of the models. In 2.36 minutes, the ResNet-18 achieved a 98.03% overall accuracy rate in classifying 600 fruit photos based on both genotype and maturity. The limited dataset used in study, and lack of explainability.

Behera, S. K. et al. [49] (2021) suggested a system to classify maturity status of Papaya fruit, using ML and Transfer-Learning. The machine learning approach evaluates HOG, GLCM and LBP features using KNN, SVM, and Naive Bayes machine learning algorithm with various kernel functions, resulting in a total of 9 classifiers. The accuracy rate of 100% achieved by using Machine Learning and Transfer Learning, both models. Research focused solely on papaya fruits. The model is restricted to papaya fruit and the dataset consists of only 300 images which limits robustness and generalization.

Vasumathi, M. T. et al. [50] (2021) presented a system to assess diseased pomegranates and categorization of that as normal or abnormal. Implementation used Python to develop a CNN LSTM model and compared to the accuracy achieved using classifiers like SVM, ANN, and Back Propagation. For normal and pathological classification, a CNN LSTM deep learning model implemented for categorization of 6519 fruits. The data utilized is an Excel file containing nine attributes for each entry. The proposed methodology achieved 98.39% F1-score, 97.77% sensitivity, a 98.65% specificity, with accuracy as 98.17%. The proposed model is limited with one fruit and two categories, normal and abnormal.

3. RESEARCH GAP

After review of different researches to assess the fruit quality by using ML and DL it has been observed that even after good result the methods reveals several limitations related to classification type, dataset size, limited features exploration and model transparency etc., the following research gaps identified:

- **Small Datasets & Limited Generalization**

  For model training the studies used small dataset size containing fruit images up to 1500, which may lead the problem for identifying unseen fruit. Most of the studies are focusing on single fruit type like Mango, Papaya, and Pineapple etc. that are limiting to generalization feature in suggested method.

- **Multi-Fruit Scenarios and Lack of Real-World data**

  Most models are tested on single fruit images and not tested for images containing multiple fruits and field market images.

- **Limited Feature Scope and Binary classification**

  Several studies considered only the external features like size, color and defect while ignoring internal features like ripeness and sweetness etc. and performed only binary classification like good or bad and fresh or rotten, as quality attributes.

- **Lack of Explainability and Model Transparency**

  Most of the models are just providing fruit quality as good, bad, fresh or rotten without providing interpretability or explainability which may lead to lack of trust.

- **Performance and Efficiency Issues**

  Despite providing good accuracy, suggested models suffering with higher computational cost and providing slow classification speed that are limiting to real time applicability.

4. OBJECTIVES

By defining precise goals to direct the research for measurable, achievable, relevant and time bounded criteria, the study's objectives serve as well-organized framework. The following objectives will focus in the current research.

1. To study and analysis of current techniques for evaluating fruit quality, highlighting their strengths and limitations to justify the present study.

2. To design an efficient model for fruit quality assessment strengthening small scale agriculture practices, using deep learning techniques.

3. To compare proposed model performance with respect to existing model.

5. METHODOLOGY

The systematic plan or strategy that will follow is discussed in this section. How the research is carried out, including the tools, techniques, procedures, and approaches applied to achieve the objectives of the study.

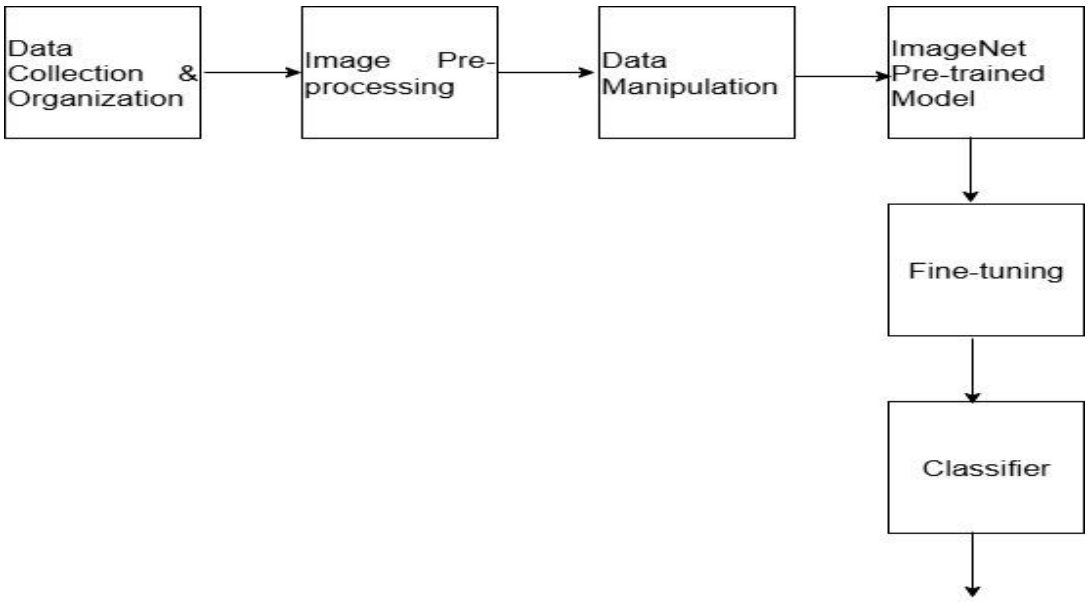


Figure 5.1: Flow of methodology

The research follows an experimental framework under a quantitative paradigm, supplemented by a minor qualitative component for interpretability evaluation. The methodological flow of suggested model represented in Figure 5.1 is as following:

- **Data Collection & Organization**

To develop fruit quality assessment model fruit(s) image data from primary/secondary (Kaggle or Research repositories) data source will be collected and arrange in folder structure so that it can be analysed or used for research and decision-making.

- **Image Pre-processing**

Collected images will be pre-processed for uniformity in term of color, size and format of images, before to manipulation.

- **Data Manipulation**

Dataset will be divided into three parts namely validation, train set and test set to support model learning.

- **ImageNet Pre-trained Model**

ImageNet dataset is huge dataset of labeled images designed for image classification and object recognition. The ImageNet Pre-trained model(s) that will be best suited for aimed model development will be use.

- **Fine-tuning**

  The selected pre-trained model will be fine-tuned by retraining its deeper layers on the fruit image dataset. This adaptation enhances the model's ability to learn fruit-specific features.

- **Classifier**

A suitable classifier (e.g., SoftMax layer, fully connected dense layer, or custom classifier) will be used to categorize fruit images into their respective quality. The optimal classifier will be selected based on accuracy, robustness, and performance on test data.

The proposed system design technique will be done in three different phases as following:

Phase 1: Data Acquisition and Preparation

Different previous research will explore and focus for availability of data source with size of dataset that best fit to the model requirement after that the following steps will perform.

- Data Collection & Organization
- Image Pre-processing
- Data Manipulation

Phase 2: Model Design

After data acquisition and preparation for model the next steps of model design are following:

- Use of ImageNet pre-trained model
- Fine-Tuning of model

Phase 3: Classification, Quality Prediction and Comparison to available model

This will be the last phase in which the classification process will be perform by using optimal classifier to predict fruit quality and the designed model will be compared with existing model(s) with respect to performance.

6. WORK PLAN OF THE RESEARCH

Research Activity(In Months)	6	12	18	24	30	36	*
Course Work	Completed						
Literature Survey							
Methodology Steps							
Quarterly Reports			Phase 1: Data Acquisition and Preparation	Phase 2: Model Design	Phase 3: Classification, Quality Prediction and Comparison to available model		
Communication of Papers			Review Paper in conference	Paper in Journal	Paper in Journal		
Preparation of Final Thesis				Thesis writing			
Submission of Thesis						Thesis Submission	

7. REFERENCES

1. Wang, H., Peng, J., Xie, C., Bao, Y., & He, Y. (2015). Fruit quality evaluation using spectroscopy technology: a review. *Sensors*, *15*(5), 11889-11927.

2. https://www.kaggle.com/datasets/sriramr/fruits-fresh-and-rotten-for-classification.

3. Ziv, C., & Fallik, E. (2021). Postharvest storage techniques and quality evaluation of fruits and vegetables for reducing food loss. *Agronomy*, *11*(6), 1133.

4. Lv, Y., Ren, X., & Ding, Y. (2024). Recent Advancements in Postharvest Fruit Quality and Physiological Mechanism. *Horticulturae*, *10*(10), 1085.

5. Si, W., Xiong, J., Huang, Y., Jiang, X., & Hu, D. (2022). Quality assessment of fruits and vegetables based on spatially resolved spectroscopy: A review. *Foods*, *11*(9), 1198.

6. Liu, J., Sun, J., Wang, Y., Liu, X., Zhang, Y., & Fu, H. (2025). Non-Destructive Detection of Fruit Quality: Technologies, Applications and Prospects. *Foods*, *14*(12), 2137.

7. Ni, P., Niu, H., Tang, Y., Zhang, Y., Zhang, W., Liu, Y., & Lan, H. (2023). Bibliometrics and visual analysis of non-destructive testing technology for fruit quality. *Horticulturae*, *9*(10), 1091.

8. Dhillon, R., & Moncur, Q. (2023). Small-scale farming: A review of challenges and potential opportunities offered by technological advancements. *Sustainability*, *15*(21), 15478.

9. Chuquimarca, L. E., Vintimilla, B. X., & Velastin, S. A. (2024). A review of external quality inspection for fruit grading using CNN models. *Artificial Intelligence in Agriculture*, *14*, 1-20.

10. Aksoy, S., Demircioglu, P., & Bogrekci, I. (2024). Evaluating pre-trained CNNs for distinguishing fresh vs rotten fruits and vegetables. *Journal of Applied Horticulture*, *26*(3), 361-366.

11. Palakodati, S. S. S., Chirra, V. R. R., Yakobu, D., & Bulla, S. (2020). Fresh and Rotten Fruits Classification Using CNN and Transfer Learning. *Rev. d'Intelligence Artif.*, *34*(5), 617-622.

12. Kangune, K., Kulkarni, V., & Kosamkar, P. (2019, October). Grapes ripeness estimation using convolutional neural network and support vector machine. In 2019 Global Conference for Advancement in Technology (GCAT) (pp. 1-5). IEEE.

13. Xiao, F., Wang, H., Li, Y., Cao, Y., Lv, X., & Xu, G. (2023). Object detection and recognition techniques based on digital image processing and traditional machine learning for fruit and vegetable harvesting robots: An overview and review. *Agronomy*, *13*(3), 639.

14. Bakar, M. A., Abdullah, A. H., Rahim, N. A., Yazid, H., Saad, F. S. A., & Ahmad, K. (2020, September). Development of ripeness indicator for quality assessment of harumanis mango by using image processing technique. In *IOP Conference Series: Materials Science and Engineering* (Vol. 932, No. 1, p. 012087). IOP Publishing.

15. Gonzalez, R. C. (2009). Digital image processing. Pearson education india.

16. Zárate, V., & Hernández, D. C. (2024). Simplified Deep Learning for Accessible Fruit Quality Assessment in Small Agricultural Operations. Applied Sciences, 14(18), 8243.

17. Rodellar, J., Alférez, S., Acevedo, A., Molina, A., & Merino, A. (2018). Image processing and machine learning in the morphological analysis of blood cells. International journal of laboratory hematology, 40, 46-53.

18. Fischer-Brandies, L., Müller, L., Riegger, J. J., & Buettner, R. (2025). Fresh or Rotten? Enhancing Rotten Fruit Detection With Deep Learning and Gaussian Filtering. IEEE Access.

19. Tapia-Mendez, E., Hernandez-Sandoval, M., Salazar-Colores, S., Cruz-Albarran, I. A., Tovar-Arriaga, S., & Morales-Hernandez, L. A. (2025). A Novel Deep Learning Approach for Precision Agriculture: Quality Detection in Fruits and Vegetables Using Object Detection Models. *Agronomy*, *15*(6), 1307.

20. Alves, V. C. D., de Lima, S. F., Santana, D. C., Barreto, R. F., da Cunha, R. A., da Silva Cândido Seron, A. C., ... & Mingotte, F. L. C. (2025). Predicting Pineapple Quality from Hyperspectral Data of Plant Parts Applied to Machine Learning. AgriEngineering, 7(6), 170.

21. Almutairi, A., Alharbi, J., Alharbi, S., Alhasson, H. F., Alharbi, S. S., & Habib, S. (2024). Date fruit detection and classification based on its variety using deep learning technology. *IEEE Access*.

22. Gao, X., Li, S., Su, X., Li, Y., Huang, L., Tang, W., ... & Dong, M. (2024). Application of advanced deep learning models for efficient apple defect detection and quality grading in agricultural production. *Agriculture*, *14*(7), 1098.

23. Khullar, V., Angurala, M., Anand, A., Patni, J. C., & Singh, H. P. (2024). Original Research Article Intelligent fruit quality classification system using transfer learning. Journal of Autonomous Intelligence, 7(4).

24. Zhao, M., You, Z., Chen, H., Wang, X., Ying, Y., & Wang, Y. (2024). Integrated fruit ripeness assessment system based on an artificial olfactory sensor and deep learning. Foods, 13(5), 793.

25. Tai, N. D., Lin, W. C., Trieu, N. M., & Thinh, N. T. (2024). Development of a mango-grading and-sorting system based on external features, using machine learning algorithms. Agronomy, 14(4), 831.

26. Rybacki, P., Niemann, J., Derouiche, S., Chetehouna, S., Boulaares, I., Seghir, N. M., ... & Osuch, A. (2024). Convolutional neural network (cnn) model for the classification of varieties of date palm fruits (Phoenix dactylifera L.). Sensors, 24(2), 558.

27. Karaja, M. B., & Abu-Naser, S. S. (2024). Using Deep Learning to Detect the Quality of Lemons.

28. Karthikeyan, M., Subashini, T. S., Srinivasan, R., Santhanakrishnan, C., & Ahilan, A. (2024). YOLOAPPLE: Augment Yolov3 deep learning algorithm for apple fruit quality detection. Signal, Image and Video Processing, 18(1), 119-128.

29. Sangeetha, K., & Raja, P. V. (2024, March). Classification of fruits and its quality prediction using deep learning. In 2024 5th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV) (pp. 342-346). IEEE.

30. Azadnia, R., Fouladi, S., & Jahanbakhshi, A. (2023). Intelligent detection and waste control of hawthorn fruit based on ripening level using machine vision system and deep learning techniques. Results in Engineering, 17, 100891.

31. IOSIF, A., MAICAN, E., BIRIȘ, S., & POPA, L. (2023). AUTOMATED QUALITY ASSESSMENT OF APPLES USING CONVOLUTIONAL NEURAL NETWORKS. INMATEH-Agricultural Engineering, 71(3).

32. Verma, P. K., Pathak, P., Kumar, B., Himani, H., & Preety, P. (2023). Automatic optical imaging system for mango fruit using hyperspectral camera and deep learning algorithm. International Journal on Recent and Innovation Trends in Computing and Communication, 11(5s), 112-117.

33. Mohd Ali, M., Hashim, N., Abd Aziz, S., & Lasekan, O. (2023). Utilisation of deep learning with multimodal data fusion for determination of pineapple quality using thermal imaging. Agronomy, 13(2), 401.

34. Alsirhani, A., Siddiqi, M. H., Mostafa, A. M., Ezz, M., & Mahmoud, A. A. (2023). A novel classification model of date fruit dataset using deep transfer learning. Electronics, 12(3), 665.

35. Sangeetha, M., Kannan, S. R., Boopathi, S., Ramya, J., Ishrat, M., & Sabarinathan, G. (2023, September). Prediction of fruit texture features using deep learning techniques. In 2023 4th International Conference on Smart Electronics and Communication (ICOSEC) (pp. 762-768). IEEE.
36. Jadhav, S., Naik, J., & Chumchu, P. (2023). Deep Learning Model for Fruit Quality Detection and Evaluation. *EPRA International Journal of Multidisciplinary Research (IJMR), 9*(5), 309-317.
37. Gulzar, Y. (2023). Fruit image classification model based on MobileNetV2 with deep transfer learning technique. Sustainability, 15(3), 1906.
38. Amin, U., Shahzad, M. I., Shahzad, A., Shahzad, M., Khan, U., & Mahmood, Z. (2023). Automatic fruits freshness classification using CNN and transfer learning. *Applied Sciences*, *13*(14), 8087.
39. Tapia-Mendez, E., Cruz-Albarran, I. A., Tovar-Arriaga, S., & Morales-Hernandez, L. A. (2023). Deep learning-based method for classification and ripeness assessment of fruits and vegetables. *Applied Sciences*, *13*(22), 12504.
40. Worasawate, D., Sakunasinha, P., & Chiangga, S. (2022). Automatic classification of the ripeness stage of mango fruit using a machine learning approach. AgriEngineering, 4(1), 32-47.
41. Aherwadi, N., Mittal, U., Singla, J., Jhanjhi, N. Z., Yassine, A., & Hossain, M. S. (2022). Prediction of fruit maturity, quality, and its life using deep learning algorithms. Electronics, 11(24), 4100.
42. Albarrak, K., Gulzar, Y., Hamid, Y., Mehmood, A., & Soomro, A. B. (2022). A deep learning-based model for date fruit classification. *Sustainability*, *14*(10), 6339.
43. Nithya, R., Santhi, B., Manikandan, R., Rahimi, M., & Gandomi, A. H. (2022). Computer vision system for mango fruit defect detection using deep convolutional neural network. foods, 11(21), 3483.
44. Kumar, T. B., Prashar, D., Vaidya, G., Kumar, V., Kumar, S. D., & Sammy, F. (2022). [Retracted] A Novel Model to Detect and Classify Fresh and Damaged Fruits to Reduce Food Waste Using a Deep Learning Technique. Journal of Food Quality, 2022(1), 4661108.
45. Mukhiddinov, M., Muminov, A., & Cho, J. (2022). Improved classification approach for fruits and vegetables freshness based on deep learning. Sensors, 22(21), 8192.
46. Kumar, A., Joshi, R. C., Dutta, M. K., Jonak, M., & Burget, R. (2021, October). Fruit-CNN: An Efficient Deep learning-based fruit classification and quality assessment for precision agriculture. In 2021 13th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT) (pp. 60-65). IEEE.
47. Chakraborty, S., Shamrat, F. J. M., Billah, M. M., Al Jubair, M., Alauddin, M., & Ranjan, R. (2021, June). Implementation of deep learning methods to identify rotten fruits. In 2021 5th international conference on trends in electronics and informatics (ICOEI) (pp. 1207-1212). IEEE.
48. Ashtiani, S. H. M., Javanmardi, S., Jahanbanifard, M., Martynenko, A., & Verbeek, F. J. (2021). Detection of mulberry ripeness stages using deep learning models. Ieee Access, 9, 100380-100394.
49. Behera, S. K., Rath, A. K., & Sethy, P. K. (2021). Maturity status classification of papaya fruits based on machine learning and transfer learning approach. Information Processing in Agriculture, 8(2), 244-250.
50. Vasumathi, M. T., & Kamarasan, M. (2021). An effective pomegranate fruit classification based on CNN-LSTM deep learning models. Indian Journal of Science and Technology, 14(16), 1310-1319.